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Residence and Workplace Relocation: A Bivariate Duration Model Approach

Different economic theories suggest that residential and labor market relocations are mutually related. This has been verified in various empirical studies. We analyze this relationship based on a bivariate duration model of residential and labor market mobility. This specification is motivated by a search model that allows for simultaneous search on the labor and housing market, taking commuting costs into account. We investigate this relationship by using information on job and residence durations. In order to be able to analyze properly empirical duration data, we derive the statistical distributions of interest. Our empirical results based on a Dutch sample of full-time employed workers show that residential and labor market mobility depend positively on one another, which is in line with the theoretical search model presented. Moreover, we present easy-to-interpret measures for this dependency.

1. INTRODUCTION

Recently, empirical research has provided strong empirical support for the proposition that residence and workplace location are jointly determined [see, among others, Waddell (1993)]. This implies that residential and job mobility are also mutually dependent. A number of studies have focused on this dependency from a theoretical point of view. For example, Zax and Kain (1991) have analyzed the dependency of residential and job mobility for an urban area by means of a partial equilibrium model. Zax (1994) makes a distinction between intra-regional and inter-regional moves, and shows that the relationship between job and residential mobility may be positive or negative depending on the particular situation viewed. According to Amundsen (1985), job and residential mobility are probably related as the demand for housing depends on labor income. In the current paper, we will analyze this dependency by means

This research was sponsored by the Economic Research Foundation, which is part of the Netherlands Organization for Scientific Research (NWO). The authors thank Cees Gorter for helpful comments.

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Geographical Analysis, Vol. 28, No. 4 (October 1996) © 1996 Ohio State University Press
Submitted 3/10/95. Revised version accepted 11/14/95.

of a search model, which allows for simultaneous search on the labor and housing market in a general spatial setting. In contrast to the static utility theories, which dominate the discussion about the relationship between job and residence, it is assumed that workers search for new jobs and new residences taking into account that the commuting distance might change. We show that according to this search model, job and residential mobility are positively related unconditional on commuting distance.

A natural empirical application of the theoretical search model proposed is a bivariate duration model which describes both workplace and residential relocations in continuous time, while allowing for mutual dependence of both processes over time. In both the labor market and the housing market literature there is nowadays a broad interest in duration modeling. These statistical techniques are used to describe appropriately the dynamics of employment (for example, Lindeboom and Theeuwes 1991), or residential moves (for example, Ginsberg 1979; Pickles, Davies, and Crouchley 1982; Ioannides 1987). Search theories in both fields make intensive use of duration modeling. See, for example, van den Berg (1992) who specified a structural search model for on-the-job search, or Rouwendal (1991) who examined the effect of regulations on residence moving behavior.

The relationship between job and residential mobility has been empirically verified at the level of individual decision makers in a number of studies (see, among others, Bartel 1979; Andrullis 1982; Linneman and Graves 1983; Vickerman 1984; Zax 1991; and Van Wissen and Bonnerman 1991). These empirical studies have in common that they are based on a discrete time analysis, so they focus on the interrelationship between job and residential mobility for an arbitrary fixed period (for example, one or two years). By employing duration data, however, one can estimate the same relationship without imposing this restriction. So, our aim is to estimate an empirical bivariate duration model that allows us to estimate the association between job and residential mobility.[1] We employ a data set which includes observations of elapsed employment and residence durations.[2] In order to estimate the bivariate duration model, we formulate the appropriate likelihood functions for elapsed duration data, taking nonstationarity due to time-varying entry rates and calendar dependency into account.

The paper is organized as follows. In section 2, we introduce the search model. In section 3, we derive the joint distribution of elapsed duration observations. In section 4, we construct the loglikelihood function and explain the estimation procedure. Empirical results are presented in section 5, and concluding remarks are given in section 6.

2. THE SEARCH MODEL

To understand the relationship between commuting, job-to-job mobility, and residential mobility in a general setting, we will rely on the following search model (see also van Ommeren, Rietveld, and Nijkamp 1994). In essence, it is

[1] In general, an alternative statistical approach is to use a simultaneous discrete choice model (see Zax 1991, 1994). However, discrete choice models cannot be used to analyze our data set of elapsed durations, as the period under observation is not fixed, a necessary condition for application of discrete choice models. Moreover, the theoretical link between a discrete choice model and a search model is less clear. Based on a different data, set van Ommeren, Rietveld, and Nijkamp (1995) find that bivariate discrete choice and duration model render almost identical results.

[2] For empirical applications with univariate elapsed data, we refer to Nickel (1979), Ridder and Kooreman (1983), Gorter, Nijkamp, and Rietveld (1992) and van den Berg (1992).

assumed that jobs and residences are both offered exogenously with a fixed probability, and that the individual has to decide instantaneously whether or not to accept a job or residence offer, taking into account (the change in) commuting costs. The use of search theory seems obvious, as it allows us to analyze decision making under uncertainty. Search theory may explain empirical phenomena with respect to commuting behavior which are hard to explain using static utility theory. In particular, Rouwendal (1994) shows that theories that include search by unemployed and employers are able to underpin Hamilton's (1982) finding that workers are virtually footloose. Although search theory has been less influential in explaining residential mobility behavior, researchers have become increasingly interested in this theory [see, for example, Pickles and Davies (1991), and Rouwendal (1991)].

The point of departure in this paper is that the workers search continuously for new jobs and dwellings in a stationary environment, maximizing the discounted future flow of wages and place utilities minus commuting costs, taking into account the once-only costs of changing jobs c_1, and residences c_2. We assume that workers receive job and residence offers[3] with a fixed probability. Moreover, we suppose that the arrival rates of jobs, p_1, and of dwellings, p_2, are independent, as for most occupations the supply side of the labor market and of the housing market function operate independently. We denote density functions by f_i and the corresponding distribution by F_i, suppressing in the notation that these functions are conditional on exogenous characteristics.

A job is entirely characterized by the wage, w, and the commuting costs, z. Wage and commuting costs offers are random drawings from a bivariate density function. We denote the conditional wage density function given the commuting costs as $f_{w|z}(w)$ and the marginal commuting costs density function as $f_{zw}(z)$. Similarly, a dwelling is entirely characterized by the place utility and commuting costs, and place utility and commuting costs offers are random drawings from a conditional place utility offer density function given the commuting costs $f_{r|z}(r)$ and a marginal commuting costs density function $f_{zr}(z)$. The wage w is received until a new job is accepted; similarly, the place utility r is experienced until the individual changes residence.[4] The commuting costs z are borne until either a new job or residence is accepted.

We denote the discounted income (indirect utility) received from the current wage, place utility, and commuting costs as $V(w, r, z)$. We assume that V is a continuous function. V includes the possibility of better offers in the future. All benefits (w, r) and costs (z, c_1, c_2) are discounted at rate ρ. The individual is assumed to maximize discounted income $V(w, r, z)$. The basic decision the individual has to make is whether to accept a new job or a residence offer, taking into account the expected offers in the future. The individual follows a decision rule, which explicitly depends on current wage, place utility, and commuting costs. The following decision rule can be constructed, which states which job or residence offer induces a job or residence move, and which not:

Decision Rules

Given a job offer of wage w_x and commuting costs z_x, and given the current wage w, place utility r, commuting costs z, and reservation wage $res_w(w, r, z|z_x)$:

[3] In the Netherlands, the housing market is highly regulated, and it is usually difficult to find appropriate housing. So, for the Netherlands, the assumption that individuals receive at random residential offers is thought to be plausible.

[4] The model may be extended by allowing for the possibility of stress building up, so place utility depends on the length of residence. Such a nonstationary model will not be discussed here.

change job if $w_x > res_w(w, r, z|z_x)$, otherwise do not change job.

Given a residential offer of place utility r_x and commuting costs z_x, and given the current wage w, place utility r, commuting costs z, and reservation place utility $res_r(w, r, z|z_x)$:

change residence if $r_x > res_r(w, r, z|z_x)$, otherwise do not change residence.

The decision rules imply that there exists a $res_w(w, r, z|z_x)$ and a $res_r(w, r, z|z_x)$ that determine whether w_x or r_x are accepted, conditional on z_x. The individual is assumed to maximize lifetime utility $V(w, r, z)$ by choosing the optimal level of res_w and res_r. The decision rules imply that, given a job offer, the worker is interested in (w_x, z_x), that is, the combination of the wage and commuting costs offer, and not in $w_x - z_x$, that is, the wage minus the commuting costs, because the job searcher takes into account that the commuting costs can be changed via a residence move. So, wage and commuting costs are traded off in an optimal way. Notice that if commuting costs do not play a role in the model, then $res_w(w, r, z|z_x) = res_w(w)$ and $res_r(w, r, z|z_x) = res_r(r)$, so job mobility depends only on the reservation wage and residence mobility depends only on the reservation place utility.

The hazard rate (also called the transition rate) from the present job to other jobs $\theta_w(w, r, z)$ can be written as the product of the job offer arrival rate and the conditional probability of accepting a job offer. Similarly, the hazard rate from the present residence to other residences $\theta_r(w, r, z)$ can be written as the product of the residence offer arrival rate and the conditional probability of accepting a residence offer. So,

$$\theta_w(w, r, z) = p_1\left[1 - \int_0^\infty F_{w|z}(res_w(w, r, z|y)) f_{zw}(y)\, dy\right];$$

$$\theta_r(w, r, z) = p_2\left[1 - \int_0^\infty F_{r|z}(res_r(w, r, z|y)) f_{zr}(y)\, dy\right].$$

When we assume that the individuals behave according to this search model, we can derive the distributions of job and residential durations as follows. As the hazard rates are independent of time, the job duration t_1 and the residence duration t_2 are exponentially distributed, so,

$$f(t_1|w, r, z) = \theta_w(w, r, z) \exp(-\theta_w(w, r, z).t_1);$$

$$f(t_2|w, r, z) = \theta_r(w, r, z) \exp(-\theta_r(w, r, z).t_2).$$

Van Ommeren, Rietveld, and Nijkamp (1994) derive the properties of the search model presented above. They show that $\partial res_w(w, r, z|z_x)/\partial z < 0$ and $\partial res_r(w, r, z|z_x)/\partial z < 0$.[5] So,

$$\partial\theta_w(w, r, z)/\partial z > 0;$$

$$\partial\theta_r(w, r, z)/\partial z > 0.$$

[5] The result also holds if the structural parameters, p_1, p_2, c_1, and c_2, exogenously depend on calendar time. In our empirical application, we will allow job and residential mobility to be nonstationary.

Consequently, given higher current commuting costs, individuals are more willing to accept a job offer and more willing to accept a residential offer, so job mobility and residential mobility are shown to depend positively on commuting costs.[6] Hence, job and residential mobility are positively interdependent unconditional on commuting costs, and from a search theoretic point of view, a bivariate duration model appears to be the natural model to estimate the relationship between job and residential mobility.[7] In the empirical application, we will use a bivariate exponential distribution in order to estimate the job and residence hazard rates, which enables us also to identify the association between job and residential mobility.

3. THE JOINT DISTRIBUTION OF ELAPSED DURATIONS ON JOB AND RESIDENTIAL MOBILITY

In case of univariate observations, the stochastic properties of the duration densities are well known under different forms of sampling (see, for example, Lancaster 1990). In this respect, it is useful to distinguish between stock and flow sampling. A stock sample is defined as a sample of individuals who occupy a certain state *at* a fixed point in time, for example, a sample of all individuals who have a job at time A. A flow sample is defined as a sample of individuals who enter the state *during* a fixed interval of time, for example, a sample of all individuals who get a (new) occupation between point A and B. We will now show how the density function for bivariate durations in a stock sample can be derived. First, we will derive the density function under stationarity assumptions. Later on, we will relax these assumptions.

We denote the bivariate distribution with completed duration variables t_1 and t_2 as $f(t_1, t_2)$.[8] The corresponding distribution functions are denoted by $F(t_1, t_2)$. Of course, durations have, by definition, a positive value. We are particularly interested in the joint distribution of overlapping durations. This can easily be established by stock sampling an individual *at* one point in time. In this section, we derive the distribution of the *observed* stock sampled durations.

A Stationary Environment

The duration data are assumed are to be generated as follows. Individuals enter at a constant rate q_1 state S_1 (being employed) and at a constant rate q_2 state S_2 (occupying a residence) in an interval $[a, b]$ which encloses 0. We assume that an individual who is in the two states of interest (in our case, being employed and having a residence) is randomly drawn *at* time 0 from a stock of homogeneous individuals. So, we observe two types of elapsed durations at time 0, which are denoted as p_1 and p_2. We define r_1 and r_2 as the residual durations, namely, the duration of being in the state of interest after 0. Moreover, t_i denotes the completed duration, so that $t_i = r_i + p_i$, $i = 1, 2$. Finally, we need

[6] For an *empirical* test of these theoretical results, see Van Ommeren, Rietveld, and Nijkamp (1995). They showed that job and residential mobility increase with commuting distance in line with the theoretical predictions of the search model.

[7] If commuting costs would be observed, one can, of course, explicitly model the interrelationship between job and residential mobility. If they are not observed, a positive and significant correlation between both durations can be interpreted as an indicator of the importance of commuting costs in relocation decisions. However, when there would also be other unobserved variables that affect job and residential mobility in the same direction, one may no longer interpret a positive correlation between job and residential mobility as a consequence of the importance of commuting costs.

[8] For the derivation of the distribution of the univariate duration observations, we refer to Ridder (1984).

to define the bivariate survivor function that gives the probability of survival during periods of length t_1 and t_2:

$$\bar{F}(t_1,t_2) = 1 - F(t_1) - F(t_2) + F(t_1,t_2).$$

Given the bivariate survivor function, the univariate survivor functions can be easily derived:

$$\bar{F}(t_1) = \bar{F}(t_1,0) = 1 - F(t_1) \qquad \bar{F}(t_2) = \bar{F}(0,t_2) = 1 - F(t_2).$$

The joint distribution of p_1, p_2 and t_1, t_2 is a conditional distribution. The condition is the *observation* of an individual. This means that the individual moved into the current state 1 at (arbitrary) $-p_1$ at constant rate q_1 and remained in this longer than p_1, and left at r_1. In addition, the same individual moved into the current state 2 at (arbitrary) $-p_2$ at constant rate q_1 and stayed there for longer than p_2, and left at r_2. Therefore, given stationarity, the sample density $h(t_1,t_2,p_1,p_2)$ is

$$h(t_1,p_1,t_2,p_2) = \frac{q_1 . q_2 . f(t_1,t_2)}{\int_0^\infty \int_0^\infty q_1 . q_2 . \bar{F}(s_1,s_2)\, ds_1 ds_2}$$

$$= \frac{f(t_1,t_2)}{\int_0^\infty \int_0^\infty \bar{F}(s_1 s_2)\, ds_1 ds_2}; t_1 \geq p_1, t_2 \geq p_2.$$

The denominator is the probability of observing an individual, given random sampling. This is equivalent to the sum of all probabilities that neither a quit nor a move since entrance has occurred which is equal to the sum of the probabilities of survival until the moment of observation, conditional on the entrance at arbitrary points of incipience.

The marginal distribution of p_1 and p_2 is obtained by integration of $h(t_1,t_2,p_1,p_2)$ over t_1 and t_2. We get then

$$h(p_1,p_2) = \frac{\bar{F}(p_1,p_2)}{\int_0^\infty \int_0^\infty \bar{F}(s_1,s_2)\, ds_1 ds_2}$$

where $h(p_1,p_2)$ is a proper density function because the (double) integration of the numerator is equal to the denominator. In the Appendix, we prove that the denominator of this expression equals $E(t_1 t_2)$. Moreover, we show and interpret the form of the joint distribution of observed completed durations $h(t_1,t_2)$.

A Nonstationary Environment

Stationarity implies that the probability of moving does not depend on explanatory variables that are a function of calendar time. This assumption will be too restrictive for many applications. In particular, in the labor market, it is thought that job mobility depends on the state of the business cycle. Therefore, in this section, we will extend the model explained above.

First, we allow the entry rates of entering state 1 or state 2 respectively to depend on the moment of entering, so $q_1 = q_1(-p_1)$ and $q_2 = q_2(-p_2)$. Residential mobility rates of those who live with their parents can hardly be interpreted as a result of the decision of the observed individuals to move. So, in the empirical application, we will select individuals who have left their parents' residence. Consequently, residential entry rates are zeros before individuals leave their parents' home at $-t_b$ which affects the probability of observing an individual. Information on the length of the time spell $-t_b$ can be used to correct for this potential bias.

Second, we allow the joint duration distribution to depend on calendar time, so $f = f_{p_1,p_2}(t_1, t_2)$ This specification also allows us to employ time-varying explanatory variables of which the complete historical time path is known (like age).

The $h(p_1, p_2)$ can now be derived under the assumption that individuals enter with a (time-varying) probability state S_1 at $-p_1$, and with a given (time-varying) probability state S_2 at $-p_2$, and remain in state S_1 and S_2 for more than p_1 and p_2 time units respectively. Therefore, conditional on the observation of an individual in state S_1 and S_2 and allowing for dependence on calendar time and nonstationary entry rates, the sample density $h(p_1, p_2)$ is equal to

$$h(p_1, p_2) = \frac{q_1(-p_1)q_2(-p_2)\bar{F}_{p_1,p_1}(p_1, p_2)}{\int_0^\infty \int_0^{t_b} q_1(-s_1)q_2(-s_2)\bar{F}_{p_1,p_2}(s_1, s_2)\, ds_1 ds_2}.$$

Instead of estimating the entry rates $q_1(-p_1)$ and $q_2(-p_2)$, information on the aggregate entry rates can be used to estimate the joint distribution $f(t_1, t_2)$ (see Lancaster 1990). A similar method has been applied by Nickel (1979) and Gorter, Nijkamp, and Rietveld (1992).

4. THE LIKELIHOOD FUNCTION

The choice between different types of bivariate duration distributions cannot be determined by economic theory. Ideally, a wide range of different models should be applied and evaluated. However, the type of data at hand may restrict the range of potential useful models. In our empirical application, we will use the positive stable mixing model (see Hougaard 1986; Lancaster 1990).[9] Given two parameters γ_w and γ_r, the bivariate survivor function is defined as

$$S(t_1, t_2|\gamma_w, \gamma_r, A) = \exp[-(\gamma_w t_1^{1/A} + \gamma_r t_2^{1/A})^A]$$

where A is positive but smaller than or equal to one. If A is equal to one, the durations are independent exponential distributed with parameters γ_w and γ_r, respectively. Hougaard (1986) showed that this bivariate survivor function can be derived from mixing two proportional hazard models when assuming that both contain an unobserved component which is positive stable distributed with parameter A. The positive stable mixture model allows us to test for positive association between t_1 and t_2.

In our empirical specification, we allow the parameters γ_w and γ_r to depend on calendar time and on time-varying explanatory variables. To be more specific, we suppose that at a certain point in time $-t_0$, the job parameter has changed from γ_w to γ_{w^*}, and the residence parameter has changed from γ_r to γ_{r^*}. Furthermore, we suppose that q_1 and q_2 have varied in the past, such that at time $-t_0$ the probability of becoming employed has changed from q_1 to q_{1^*}, and the probability of moving residence has changed at time $-t_0$ from q_2 to q_{2^*}.

[9] Employing a different data, set Van Ommeren, Rietveld, and Nijkamp (1995) used both the positive stable and the discrete mixture distribution to estimate a bivariate duration model. They found similar result for both distributions.

The time-varying survival functions can be readily calculated by multiplying the conditional stationary survival functions. One can distinguish four types of observations, depending on whether the observed elapsed residence and job durations are longer or shorter than t_0 (I. Both durations are shorter than t_0; II. The job durations are shorter and the residence durations are longer than t_0; III. The residence durations are shorter and the job durations are longer than t_0; IV. Both durations are longer than t_0). For example, the time-varying survival function for those observations for which the job and residence durations are longer than t_0 (Type IV) can be written as

$$\bar{F}(p_1, p_2) = S(p_1, p_2 | t_0, t_0, \theta_{w^*}, \theta_{r^*}) S(t_0, t_0 | \theta_w, \theta_r)$$

where the conditional survivor function is defined as

$$S(p_1, p_2 | t_0, t_0, \theta_w, \theta_r) = \frac{S(p_1, p_2 | \theta_w, \theta_r)}{S(t_0, t_0 | \theta_w, \theta_r)}.$$

Interpretation of the above formulae is as follows. The probability that the individual survives in both states for p_1, p_2 times respectively equals the probability that the individual has remained for t_0 time in both states given the parameters θ_w and θ_r, times the conditional probability that this individual survives in both states for more than p_1, p_2 times given parameters θ_{w^*} and θ_{r^*}, the condition being the survival for t_0 times in both states. The time-varying survival functions of the other three types of observations are special cases of the formula derived above. Finally, the loglikelihood can be obtained by adding the logarithm of the individual contributions.

Now, the parameters of interest can be obtained by maximum likelihood (ML) estimation, but also by employing a two-stage procedure as proposed by Hougaard (1986). The latter procedure is simple: first, one estimates by using ML the univariate processes *separately* using the marginal distributions $h(p_1)$ and $h(p_2)$:

$$h(p_1) = \frac{q_1(-p_1)\bar{F}_{p_1}(p_1)}{\int_0^\infty q_1(-s_1)\bar{F}_{p_1}(s_1)\, ds_1} \qquad h(p_2) = \frac{q_2(-p_2)\bar{F}_{p_2}(p_2)}{\int_0^{t_b} q_2(-s_2)\bar{F}_{p_2}(s_2)\, ds_2}.$$

Second, given the numerical estimates of the parameters in the first step, the parameter A can be estimated by maximizing $h(p_1, p_2)$ with respect to A. The essence of this procedure is that in the first step, the parameters of interest, namely, γ_w, γ_r, and A, are not identified, while the second step allows identification of these parameters. We will illustrate the identification issue of the parameters in case of a stationary environment (see section 3). Then, the marginal distribution $h(p_1)$ can be rewritten and simplified to

$$h(p_1) = h(p_1, 0) = \gamma_w^A \exp[-\gamma_w^A p_1]$$

which is an exponential distribution with parameter γ_w^A; similarly, $h(p_2)$ is exponential distributed with parameter γ_r^A. Given the two (first-step) separate estimates of $\theta_w = \gamma_w^A$ and $\theta_r = \gamma_r^A$, it is clear that the three parameters γ_w, γ_r, and A are not identified. However, joint estimation of $h(p_1, p_2)$ gives us the additional information to identify A, and therefore γ_w and γ_r. As a result, conditional on the estimates of the first step, A can be estimated. The likelihood of the second step can be compared with that of $A = 1$ (no correlation). This is a conservative test because at the true ML estimate of A the loglikelihood is higher than at the A estimated with the two-stage procedure. In our empirical application, we will use the two-stage procedure, as it is easy to apply. Moreover, two-stage procedures are more robust with respect to the restrictive assumptions of the (unknown) mixing function.

Until now, we have discussed models of homogeneous individuals. Clearly, we need to allow for observed variation of exogenous explanatory variables. The incorporation of explanatory variables x_1, which affect job mobility, and x_2, which affect residential mobility, is straightforward. This can be done in the Cox framework: the parameters γ_w and γ_r are specified as $\exp(x_1.\alpha)$ and $\exp(x_2.\beta)$ respectively. So, the hazard rate θ_w is equal to $\exp(x_1.\alpha)^A$, while θ_r is equal to $\exp(x_2.\beta)^A$. Consequently, as all the regressors are dummy variables, the (quasi) elasticity of the job hazard rate θ_w with respect to x_1 is equal to $\partial \ln(\theta_w)/\partial x_1 = A.\alpha$ and the (quasi) elasticity of the residential hazard rate θ_r with respect to x_2 is equal to $\partial \ln(\theta_r)/\partial x_2 = A.\beta$. In the empirical application, we will report estimates for $A.\alpha$ and $A.\beta$. Hougaard (1986) shows that the correlation between $\ln(T_1)$ and $\ln(T_2)$ equals $1 - A^2$, which we will use as a measurement of association between job and residential mobility.

5. THE EMPIRICAL APPLICATION

A Dutch data set which contains full information on relocation behavior of employment and residence over time has been collected in 1984 and is called ORIN. It is a lifestyle survey based on a sample of 1,601 individuals aged 18–54 years in 1984. Retrospective questions, including household, labor, and migration biography, covered the period 1977–1984. The survey includes many socioeconomic characteristics of individuals, their job, and their residence. The data set includes information on both the elapsed duration of work and the elapsed duration of residence; however, information about commuting costs is absent. We have selected only full-time employed workers aged above 26 and who did not live with their parents, so 434 individuals were left. Information about the exact moment the individuals left their parents' residence is available. Our choice of the explanatory variables to characterize the differences in job and residential mobility is discussed below.

Job Mobility

Educational achievement will probably influence job mobility, although from a theoretical point of view it is not clear whether there is a positive or a negative relationship. To understand the relationship between education and job mobility, it seems useful to distinguish between vertical and horizontal job mobility. Vertical mobility includes job moves to jobs with higher wages and/or more opportunities ("career"). Horizontal mobility includes job moves which do not lead to such an improvement. Vertical mobility will probably increase with higher education, as there are more opportunities to grow and more variation in wages. So, education is considered to be a form of (irreversible) investment which increases the return on the hours worked and offers more opportunities for an upward career. On the other hand, horizontal mobility decreases with education according to the segmented labor market theory (Doeringer and Piore 1971). For example, poorly educated individuals operate more frequently in a market with temporary contracts than higher educated people. In conclusion, whether education has a positive or a negative effect on job mobility is finally an empirical matter, that is, to be investigated by applied work. The following two levels of education are included in our model: one group with university or polytechnic education and one group with secondary school and vocational education. The individuals having only primary school are in the reference group.

Not only formal education, but also on-the-job experience and personal skills determine the level of relevant skills for a job. The level of skills of an individual is reflected in the position within the firm, which influences job mobility in similar ways as formal education. In addition, hiring and firing costs will depend on the position of the employee within the firm, which will affect quitting behavior. Three different levels of positions are incorporated in the model: one group consists of middle-level employees. Another group consists of lower-level employees and skilled workers, and the third group contains nonskilled workers. The reference group consists of managers/directors, professionals (for example, lawyers) and higher-level employees.

It is well known that age has a strong effect on the probability to leave a job: young people move more as they have more opportunities to climb (Lindeboom and Theeuwes 1991). We include a dummy for respondents between 32 and 36, between 37 and 44, and above 45; young persons are in the reference group. We also include a dummy for gender to capture observed difference in the behavior of males and females. We also include a dummy West to correct for potential differences between regions in order to take into account the typical structure of the regional labor market. In the western provinces unemployment/vacancy ratios are lower than in the rest of the Netherlands (see, for example, Gorter, Nijkamp, and Rietveld 1992). Finally, we include a dummy for the period 1979–1984 to capture business cycles effects. In the Netherlands, job mobility has been extremely low due to a downturn of the economy during that period. Ignorance of business cycle effects is therefore likely to bias the results.

Residential Mobility

Residential mobility can best be understood if the residence is envisaged as a local good, which cannot be transferred to another location. Given a change in the demand for residential space, or given a better residential offer, one would move if the gain of the move is higher than the moving costs. One expects that some variables particularly influence the change in demand for a residence, while others will influence more the moving costs. It is well known that the change in the demand for a residence depends on the stage in the life-cycle. In general, younger people experience more changes (because of marriage/divorce, birth of children, changes in income), so that a priori one expects a strong effect of age. Therefore, we have included the age dummies as described above. Another important explanatory variable used in the residential mobility literature is educational achievement (for example, Linneman and Graves 1983). We have included also level of position as a proxy for income. We included one variable for those who live in the West of the Netherlands in order to take into account the typical structure of the regional housing market. The western provinces are most highly urbanized and characterized by a high share of the (regulated) rental sector. Further, a dummy for persons who call themselves religious is used to test whether social bonds are higher for this group, which may have a negative impact on residential mobility (Linneman and Graves 1983). Finally, we include dummies for gender and home ownership.[10]

Information about the aggregate entry rates $q_1(-p_1)$ and $q_2(-p_2)$ is obtained

[10] Strictly speaking, home ownership is endogenous, because mobile persons prefer renting above owning (see Boehm 1981).

TABLE 1
Estimation Results of Job and Residential Hazard Rates

	Job mobility	Residential mobility
*Constant	−1.80 (0.29)*[a]	−1.04 (0.20)*
*Gender:		
male	−0.21 (0.11)*	−0.04 (0.13)
*Age:		
32 < age < 36	−0.48 (0.17)*	−1.01 (0.17)*
37 < age < 44	−0.96 (0.16)*	−1.05 (0.15)*
age > 45	−1.01 (0.19)*	−1.57 (0.18)*
*Position at Work:		
middle level	−0.06 (0.19)	0.35 (0.17)*
lower level	0.04 (0.31)	0.17 (0.22)
unskilled worker	0.01 (0.24)	0.09 (0.16)
*Education:		
secondary	0.15 (0.19)	0.00 (0.06)
university/poly	0.47 (0.20)*	0.02 (0.14)
*Religious		−0.22 (0.10)*
*Region West	−0.11 (0.08)	0.13 (0.12)
*Home Ownership		−0.05 (0.16)
*Period		
1979–1984	−1.39 (0.40)*	−0.21 (0.22)
*A	0.88 (0.04)[c]	
correlation($\ln(T_1), \ln(T_2)$) =	0.25 (0.09)*	
log likelihood =	−4.660	

a. standard deviation between parentheses.
*. coefficients are significant at the 5 percent level.
c. significantly different from 1.

from other data sources (Mekkelholt 1993 and CBS 1992). Unfortunately, in the Netherlands, aggregate labor mobility data are extremely scarce, have not been continually collected, and different data sources disagree (see Mekkelholt 1993). Moreover, in the Netherlands, although internal migration figures are available for more than a century, the aggregate number of intramunicipal changes of residence before 1977 are unavailable, which are, in principle, needed. The reported results are based on the assumption that the job entry rate q_1 before 1979 is 30 percent higher than after 1979, and the residential entry rate q_2 is constant. Given the uncertainty about the validity of the aggregate data, we have done a sensitivity analysis. It appears that most results are hardly affected by the choice of the aggregate job or residential entry rates.[11]

We have estimated residence and job mobility separately by using the two-step procedure described before. Estimation results are presented in Table 1. The reported coefficients $A.\alpha$ and $A.\beta$ may be interpreted as (quasi) elasticities of the marginal job and residential hazard rates with respect to the regressors. The results indicate that age significantly affects job mobility: young persons are very mobile compared to older persons (see also van den Berg 1992; Hall 1982). Educational achievement appears to be significant, as those with an university or polytechnic degree change jobs more frequently. The position level at work does not seem to affect job mobility significantly. Similar results for the Netherlands were found by Kerckhoffs and Wolfs (1991) and Lindeboom and

[11] The exception is the estimate for gender explaining job mobility. Given constant job entry rates, gender effects are insignificant, while the reported results that assume nonstationary job entry rates clearly indicate that males move less.

Theeuwes (1991). In line with Lindeboom and Theeuwes (1991) and van Ommeren, Rietveld, and Nijkamp (1995) we find significant effects for gender. Finally, the stylized fact that job mobility varies over the business cycle is confirmed by the data, as the results clearly show that job mobility was substantially lower between 1979 and 1984 compared to the period before, in line with information on aggregate mobility.[12]

The results for the residence mobility are plausible, as signs of most coefficients have the expected direction. As explained above, young persons move more frequently in the housing market than older persons. Religious persons are less mobile, probably because of higher psychical moving costs due to strong bonds to community members. Education appears to be insignificant, but the estimates for the level of position show the form of a U-curve.

This result seems to contrast the findings of other studies.[13] Apparently, in the Netherlands, the effects of education and position at work on residential mobility are not univocal, which could be due to the fact that the housing market is highly regulated.[14] In particular those with less education or lower positions are more likely to be restricted to the regulated housing market which restricts moving.[15] On the other hand, workers with high positions change residence less frequently than others, probably because they occupy a larger dwelling with higher moving costs. We find that home ownership has negative, but very insignificant, effects on residential mobility. The estimated effects on residential mobility for the region West is insignificant. Finally, we find that the calendar effects are insignificant, which is in agreement with aggregate data on residential mobility.

A significant positive relationship between residence duration and workplace duration was found, as the parameter A is significantly different from one (A equals one under the hypothesis of no dependency). The studies mentioned in the introduction do not provide measures of association that are easy to interpret; however, the use of a duration model allows us to calculate the correlation between the logarithms of job duration and residence duration, conditional on the explanatory variables included in the model. According to our data, the correlation between the logarithms of the two durations of interest is approximately 0.25. The LR-test statistic has a $\chi^2(1)$ distribution under the hypothesis of no dependency. The value of this statistic equals 9.11, which is above the 95 percent critical value of this distribution (which is 6.63). As a result, residential mobility and job mobility appear to be positively correlated. The strength of the relationship between job and residential mobility can be also be clearly demonstrated by calculating conditional and unconditional expectations. For example, we find that the expectation of employment duration of a specific individual[16] is 5.8 years, while the (conditional) expectation of the same individual who has not moved residence for twenty years, is around 7.0 years.

[12] In an earlier version of this paper, business cycle effects were ignored which seriously biased the empirical estimates. We thank one of the anonymous referees for bringing this to our attention.

[13] For example, Van Ommeren, Rietveld, and Nijkamp (1995) investigated the determinants of residential mobility, and found no effects for the number of subordinates, but low (although significant) educational effects.

[14] For example, 95 percent of all rented residences were subject to some form of price regulation in the Netherlands. Moreover, the regulations outlined by the (local) government often determine the tenure of the residences.

[15] An alternative explanation might be that unskilled workers move their residences less often, as moving costs are relatively high compared to their incomes.

[16] The individual is a male, younger than thirty-six years, with a high position at work, with a low educational level, and not religious.

6. CONCLUDING REMARKS

We have used a bivariate duration model to estimate the relationship between job and residential mobility. This specification is motivated by a search model which allows for simultaneous search on the labor and housing market, taking commuting costs into account. The statistical advantage of a continuous time analysis compared to the more common discrete time analysis is that no (arbitrary) assumptions are needed about the interval in which job and residential mobility are related. Moreover, duration models allow us to analyze observations of elapsed employment and residence durations when discrete time methods cannot be applied. Our empirical results based on a Dutch data set suggest that residential and labor market mobility depend positively on one another, which is in line with the search model presented. We present easy-to-interpret measures of this correlation. For example, we find that where the expected employment duration of a specific person is 5.8 years, the expectation of the same individual who has not moved residence for twenty years, is around 7.0 years.

In line with other studies we find that gender, age, education and business cycles are important determinants of job mobility. According to our data, residential mobility is mainly affected by age which represents the stage in the life cycle. However, we also find that religious persons change residence less often. Furthermore, we conclude that in the Netherlands the effects on residential mobility of education, position at work, and home-ownership are not univocal, which could be due to the fact that the housing market is highly regulated.

APPENDIX

When one observes the residual durations after 0, one obtains t_1 and t_2. The form of the joint distribution of observed completed durations can be shown to be

$$h(t_1,t_2)=\frac{t_1t_2f(t_1,t_2)}{\int_0^\infty\int_0^\infty 1-F(s_1)-F(s_2)+F(s_1,s_2)\,ds_1ds_2}.$$

The interpretation of $h(t_1,t_2)$ is as follows [see Ridder (1984) for the univariate model]. The density function $h(t_1,t_2)$ gives the equilibrium distribution of the lengths of both completed durations drawn at random from all durations that contain respectively the time 0 at which the sample is drawn. The density $f(t_1,t_2)$ gives the joint distribution of both completed spells which start at time 0. The factor t_1t_2 in $h(t_1,t_2)$ is included in the likelihood because longer durations have a larger probability of being sampled than shorter ones. In fact, the length-biased sampling correction is proportional to its durations in the univariate case, and includes the factor t_1t_2 in the bivariate case.

The joint distribution $h(t_1,t_2)$ can be derived from $f(t_1,t_2)$ by integration over p_1 and p_2. This means that we have to prove that $h(t_1,t_2)$ is a proper joint density function. One might want to check whether the double integration of the numerator, which is equal to $E(t_1t_2)$, equals the denominator. This can indeed be shown by the following approach. Double integration by parts of two arbitrary functions A and B (^{x}, ^{y} denotes partial derivation with respect to x,y) gives the identity

$$\int\int(AB)^{xy}=\int\int A^{xy}B+A^xB^y+A^yB^x+AB^{xy}.$$

When one chooses $A=F$ and $B=t_1t_2$ the desired result is obtained.

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